Search and Vacancies in the French real estate market

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I. Introduction

Labor market was not the first example of a market with search frictions Dale T. Mortensen came up with in the lecture he delivered in Stockholm when he received the Nobel Prize, together with Peter A. Diamond and Christopher A. Pissarides, for the so called DMP model. Away from the application field he received the supreme distinction for, he started his address telling the story of his own story of the purchase of a new apartment “with a view of Lake Michigan” and the sell of his old house. In his own words : “All of the time and effort spent by both sides of such a transaction represent search and matching frictions.”

Indeed search and matching models have been apply to the real estate market for more than 20 years now, from the first unilateral search models (see Salant 1991) to recent sophisticated directed search (see Carillo 2013 or Merlo and al. 2015) or random matching models (Genovese and Han 2012). If the selling side as been largely studied both in a theoretical perspective and an empirical one, the literature is more scarce regarding home buyers. The main reason is that buyers, contrary to sellers, do not declare themselves through listing; making hard to track their search or even just to count them. A solution to fill this gap would be to use user’s data from internet real estate sites as Piazzesi and al. (2015) do using *trulia.com* email alert subscriptions.

In this paper a random matching model is, to my knowledge for the first time, confronted with a direct measure of the buyer-seller ratio in the housing market. Through the data collected on the french real estate web platform *MeilleursAgents.com*, I am able to track over a four years period, on a quarterly basis, how many buyers and sellers were active in more than 250 cities of the Paris Area and relate these measures to the number of sales and the housing prices dynamics in these cities.

As in Piazzesi and al. (2015), I record for an upward sloping Beveridge curve, a positive correlation between supply and demand, for the Paris housing market. This positive correlation appears to be true both across cities, at a given date, and over time, for a given city. In line with the matching theory, I measure that sales volume and prices evolution are positively correlated with the market tightness. Interestingly volumes seem more reactive than price to evolution of the buyer-seller ratio as the lagged market tightness appears to have weaker effect on the rotation rate than on price variations. Moreover, I measure that if its effect of volume is symmetrical in a “hot” or “cold” market, the magnitude and the statistical significance of the market tightness effect on price are stronger in the former than in the latter.

The rest of the paper is organized as follow, section 2 presents the literature my work is related to. Details on how the dataset I used have been collected and a static description of it are given in section 3. Empirical results are presented and discussed in section 4. Section 5 concludes.

II. Literature

The work presented here fall within the rich literature of search and matching models applied to the housing market. From Wheaton (1990) this framework has delivered many important results in our comprehension of the forces that drive the real estate market and a full literature review would be out of the scope of the present paper, see Han and Strange (2015) for a comprehensive uptodate survey. Here I chose to mainly focus on theoretical and empirical studies in which market tightness plays a central role.

To my knowledge the first to look at housing with a search and matching approach was Wheaton (1990). His motivation to draw such model from the labor market literature, the so called DMP model, is routed in four facts about housing markets. First they exhibit structural vacancies rates (i.e. the share of the housing stock that is "for sale" at any given moment in time) which are proper to each market. Second, variation around these structural rates impact sellers time on market and prices. Third, most transactions are the consequences of turnover (i.e. persons selling their old home to buy a new one). Finally housing supply, construction, reacts slowly to market conditions and thus the housing stock is constant in the short run. These facts are explained by a "stock-flow" matching model with both numbers of housings and households are fixed in the short run and prices adjustment equates the demand and the stock of "for sale" homes.

The Wheaton model can be summarized as follow. The market is composed of households and houses of two different types. When a type I (resp. II) household lives in a type I (resp. II) house, it is "matched" otherwise it is "unmatched". Household randomly switch type following a Poisson process of parameter proper to the market (its turnover rate). An "unmatched" household search for a suited home. The search is costly. Its cost determines the search effort and the buyer's willingness to pay. Sellers are buyers who have found a new home that fits them and put up their old one for sale. Thus there is more units than households. The seller's reservation price is determined by the cost of search and their expected sales duration.

In the short run, at equilibrium, the key parameter is the vacancy rate. As it increases (resp. decreases), sellers' time on market increases (resp. decreases) and sales prices decreases (resp. increases). In the long run, new homes are built, until the units marginal construction cost reach the "expected price", which is the expected price discounted by the expected sale duration. With a reasonable set of parameters, the model provides predictions that match with the stylized facts, in particular : sales prices are sensitive to even small change in the vacancy rate, a higher turnover rate imply higher structural vacancy rate and thus higher prices.

If Wheaton work key variable is vacancy, subsequent studies focus on the market tightness or buyer-seller ratio. It allows to study a more general market, free of some strong hypothesis, such as fix number of homes and households or compulsory "buying first then selling" strategies. Novy-Marx (2006) proposes a model for housing market, directly derived from labor DMP models that aims at explaining why housing markets are more volatile than fundamentals. It shows how market participants optimal individual responses reinforce initial shocks by dipparting himself from the classic infinite elasticities of participant market entry.

He presents a classic mating game in which seller-buyer encounter rate is homogenous and of degree one in the relative number of buyers and sellers, i.e. the market tightness. The matching is stochastic: the surplus of the transaction is reveal to both participants after their encounter, thus not all matches lead to a transaction. If it does, the surplus is divided following a Nash bargaining. Finally the entry rate in the market is proportional to the participants expected participation values. At equilibrium, exit rate (i.e. sales number) equals the entry rates of both seller and buyer.

In this framework, the market tightness is log proportional to the relative level of buyer over seller supply curve. How it is sensitive to it depends on participants entry rate price elasticity. The more they respond to their expected participation value, the more the market tightness is stable. It also provide insightful predictions on the impact of market tightness on market outputs. First, the relative time on market of buyers over seller equals the market tightness. Then, considering some reasonable parameters, it predicts numerically that the transaction threshold is, weakly, increasing with the buyer-seller ratio. Finally, the same parameters leads to a almost one to one negative relationship between sale price and sales duration.

The theoretical literature on the subject is quite rich and the previous example are just sample (see for example Krainer 2001 or Albrecht and al. 2007), on the empirical side however proofs are more scarce. Two noticeable exceptions are Genovese and Han (2012) and Piazzesi and al. (2015). The former present the first estimate of a matching function in housing, to my knowledge. The authors confront a matching model close to the one introduced by Novy-Marx (2009) to a survey on search duration of both buyers and sellers across US metro area, over 20 years. They show how search behavior and thus market outcomes tend to overshoot a demand shock as they respond more to change in the demand level than to the level of the demand itself.

The dataset they assembled regroup US National Association of Realtor buyers and sellers surveys from 1987 to 2008 and Metropolitan Statistics Area that record, among other things, for population and income for US metropolitan areas annually. From the surveys they draw three metrics to describe the search behaviour : the seller time on market, the buyers time on market and the number of houses visited prior to the purchase by a buyer. The study focus on the measure of these liquidity measures reactions to housing demand variation, which is approached by level and yearly variation of income and population in the considered metro areas.

On the theoretical side, a classic DMP model with stochastic matching is developed. As in Novy-Marx (2009) the authors derive that the market tightness equal the buyers' time on market over the one of sellers. They differs from Novy-Marx (2009) by considering an infinite elasticity of buyer supply with regards to their participation expected value. They also extend it to incorporate a lagged response of sellers' reservation prices to demand shocks and show how, in the short run, market liquidity measures tend to overshoot the new equilibrium.

From multiple panel regressions, they find that population and income level and variation have a negative effect on their three liquidity measures, with the buyer time on market being more sensitive. The market tightness is derived from the ratio of buyer over seller time on market. Seller and buyer contract hazard rate are approached by respectively the logged number of houses visited and the logged of the inverse of this number. They find, as predicted, that demand shocks impact positively the market tightness and seller hazard rate and negatively the buyer hazard rate. As expected the short run effect is systematically stronger than in the long run. Finally they are able to measure a the seller contract elasticity to the market tightness. They find a 0.84 figure, indicating a -0.16 buyer hazard rate elasticity, all consistent with the theory.

The only other empirical study on the subject is particularly interesting to us as it also uses internet data to characterize search and matching in the housing market. In Piazzesi and al. (2015), the authors use the email alert subscriptions and listings posted on the website *trulia.com* to study the San Francisco Bay Area market. Thus they proposed the first proxy measure to market tightness in the housing litterature, which is combined with officials sales and housing stock records. Their main focus is to show how the partial segmentation of the housing search can explained a negative relationship between search and vacancy between cities but a positive one within the cities real estate markets.

The dataset, constituted by more than 23,000 search alerts and 40,000 “for sale” listings collected over 6 years, is explored over several dimensions. First, patterns from buyers’ housing search are revealed. It occurs along three main dimensions : geography (zip code), price and size (number of bathrooms). A vast majority of prospective buyers searches over contiguous area but some searches across a broader range of segments. Those broad searchers appear to be more active in cheaper segments than in expensive places.

Second, the authors proposed a segmentation based on those search dimensions of the Bay Area real estate market into 564 segments. Comparing stock, inventory (i.e. vacancy) and turnover in those segments over the 2006-2012 period with the email alert subscription they are able to build a weighted searcher per house for each segment for the period. Their main empirical finding is that they observed an inverse Beveridge curve, a positive correlation between numbers of buyers and sellers, across segment within a city but more “classic” Beveridge curve, negative correlation, when aggregating at the city level. A matching model that lets buyers search in several segments when sellers are tied to only one is proposed to explain this phenomena. It shows that in a perfectly segmented market, for example between cities, the most expensive segments are both more stable and popular generating a downward sloping Beveridge curve. On the contrary, within partially segmented market (within cities), broad searchers will tend to look more actively in larger inventory of the less stable segments, generating an upward sloping Beveridge curve.

III. Data

In this section I describe how I combined records of users activities on the french real estate platform MeilleursAgents.com and notary sales register to document the matching process in the Paris urban area housing market.

Market tightness measure

The main difference between this research and what already exist in the literature is that through internet activities, I were able to build a measure of the housing market tightness for 250+ cities in the Paris area from 2014 to 2017. This measure is done over time, on a quarterly basis, allowing for a dynamics analysis, contrary to Piazzesi and al. (2015) that measures the market tightness once for a six years periods. The website used for that measure, *MeilleursAgents.com*, makes various real estate information available online: price maps, indexes and an automated valuation model. With 2 millions monthly unique visitors and 200,000 property price estimates every months it claims to be the national leader for “Real estate online estimation”. This claim being true or not, its penetration rate is sufficient to consider the measure of its users activities as significant.

The valuation tool available on the website appears to be a good spot to measure how many buyers and sellers are active in a market at a given time. This valuation tools give to user an estimate of any housing unit based on its address and a description of the property.To get an estimate, the user need to give an address and fill a form (screenshots of the entire funnel are available in the appendix) that asks for basic characteristics such as livable surface, number of rooms, floor and number of bathrooms; and more advance ones: presence of an elevator, of a cellar, recent facade renovation etc... All those characteristics are used by a hedonic model combined with spatial econometrics models to compute a predicted market value.

The user has also to specify the reason she wants an estimate of the property. If she declares to own the property, she is asked the property usage, if the property is currently on sale, or if he wish to sell it in a near future, and the date and the price of its acquisition (optional). If she does not owned it, she is asked if she is currently looking to buy a home and, if so, at what stage she is in her search. She is also asked to give an email address, which allow me to uniquely identify her. Through the response of these questions I am able to perform a measure of the relative size of the two populations of interest. More precisely :

- A user is considered a seller if :
    - she indicates she owns the described property
    - she answer to the question “Do you consider selling this property?” by :
        - “Yes, I have already start to sell it”
        - “Yes, as soon as possible”
        - “Yes, within three months”
- A user is considered a buyer if :
    - she indicates she does not own the described property
    - she answers to the question “Why do you estimate this property?” by “ I wish to buy”
    - she answers to the question “Where are you at with you search?” by :
        - “I am starting”
        - “I am actively searching (more than 5 visits)”
        - “I made an offer”

Those “buyers” and “sellers” are then aggregated along three dimensions: temporal , geographical and property typology. Thus I get a measure of the market tightness for every type of property (apartment or house), for every zip code (that correspond each to one municipality) and every quarter (from Q1-2014 to Q4-2017).

Questions about those data reliability have to be tackled. First, one should point out that users can declare anything about their project. Indeed I use pure declarative data here but two reasons plead for the good faith of users. First they have no incentive to lie about their project to buy or sell a house. If anything I can fear underdeclaration of the users plans as they can be reluctant to disclose their projects to a commercial website. Second, I get a confirmation, at least for the sellers, that what they indicate is real in the very existence of *MeilleursAgents.com* as a company, for now more than 10 years, as its primary business model is to call back the “sellers” and to connect them with real estate agents for a cut on the commission agents get after the sell.

Another point might be wondering. Why don’t I use listing directly to measure the supply side of the housing market? First reason is that there is no such thing as a Multi Listing Service in France. Thus no listing portal can claims to capture the whole market. Even if some could be consider big enough to capture a statistically significant portion, I have no way to measure the demand side on those portals. To measure demand and supply at the same point offers advantages. If no one can reasonably think that MeilleursAgents.com captures the whole market, there is no *a priori* reason to believe it is more representative of either buyers or sellers as a price estimate is an information that both side of the transaction seek. One not satisfied with this argument, who believe than one side is more present than the other, should be convinced that if there is some bias, I have no reason to believe that it is not constant and thus could be easily control for.

Rotation rate and price evolution

To confirm the predictions made in the literature, this measure of market tightness need to be related to market outcomes: prices and volumes. Here I turn to notary databases and census data from INSEE (French Census Bureau).

Notary databases record for all transactions that occur in France at the exception of newly built properties. In the Paris region, these databases as been digitized from early 1990’s. Every transaction is precisely describe: amount, date, description of the property. Note that the date recorded is the date of the official notary act that occurs weeks after the sale agreement. This time laps is on average three months (source Notaires de France), thus I consider the sale agreement date as the recorded date in the notary database minus three months. Aggregating along the same dimensions as above for the count of buyers and sellers, I easily get the numbers of housing sales for every typology of property, quarter and municipalities considered above.

Rotation rate (i.e. number of sales per hundred units available) is then easily compute thanks to public statistics on housing. I use the latest “Base Logement” of INSEE. It indicates how many apartments and houses there was in every municipalities in 2015. The real estate stock evolving slowly, I use the data from 2015 for the whole four years period I study.

I also want to measure the effect of market tightness on price. MeilleursAgents.com produce price indexes for almost all cities in the Paris area based on the same notary databases. These indexes are computed for apartments and houses separately, as long as the stock of each type of housing is sufficient (more than 1000 units). They are computed on a quarterly basis. The hedonic method used to produce them is detailed in the appendix.

Summary statistics

Aggregation of these different data sources already offers insights about the real estate market matching process. To be considered in my dataset, for a given quarter, a market segment have to have at least one seller and one buyer recorded on MeilleursAgents.com, to exhibit at least one sale and to have a price index available. Overall it accounts for 5,641 data points spread over 264 municipalities, 145 for which both segments (apartments and houses) are studied, in 117 only apartments are considered and only one where the sole house segment made it to our dataset.

Table 1 presents summary statistics for the main variables.

	mean	std	min	25%	50%	75%	max
#sales	60	82	1	19	32	62	730
#buyers	20	46	1	3	7	14	409
#sellers	30	48	1	9	15	28	479
#units	11275	17237	1009	3619	6008	11138	144219
rotation rate	0.60%	0.31%	0.05%	0.41%	0.54%	0.71%	4.36%
vacancy rate	0.27%	0.11%	0.02%	0.19%	0.25%	0.33%	1.19%
demand per units	0.14%	0.10%	0.01%	0.07%	0.12%	0.20%	0.77%
market tightness	0.59	0.47	0.03	0.27	0.50	0.78	9.00
price index	98	4	82	96	98	100	124
volume quarterly variation	10%	54%	-90%	-19%	0%	26%	1100%
price quarterly variation	0.04%	1.04%	-5.36%	-0.53%	-0.02%	0.57%	5.53%

Table 1 : Summary statistics of the dataset

The Paris area housing market offers a variety of situations, from the almost 150,000 appartements of the Paris 15th arrondissement to the barely 1,000 in Chessy in the far east suburb. With a third quartile of 11,138 units compare to the 11,275 on average, most of the segments studied are small but the distribution is highly skew on the right side by large Paris arrondissements or the dense close suburban municipalities like Boulogne-Billancourt, Courbevoie or Saint-Denis.

The size of the housing stock considered, there is no surprise in the low average number of sales quarterly recorded of 60. Once again the distribution is skewed by large municipalities. The maximum of 730 sold apartments is reached in the 18th arrondissement in the last quarter of 2016 when the third quartile is 12 times less than that, barely above the average. In contrast the quarterly rotation rate, i.e. number of sales per units, is more evenly distributed with half the segment/quarter between 0.41% and 0.71%. The 0.60% average which would correspond to a 2.4% yearly rotation rate seems a little low compared to national aggregated statistics that range from 2.3% to 3% over the period (source French Housing Ministry). Note that extreme values differ strongly from the average, which is the result of some small segments mechanically more volatile.

Price indexes, based in Q4-2013, average to 98 with most quarterly variations included between +0.5% and -0.5% and seems overall stable. Taken year by year two periods emerge : 2014-2015 that exhibits to a decrease in housing prices and 2016-2017 in which prices rise (see table 2 and below for a more detailed analysis of the market dynamics).

As far as my mesure of the market tightness is concerned, the first remark is that, as expected, *MeilleursAgents.com* does not capture the whole market as both sellers and buyers count are significantly lower than the number of sales as they average respectively to 30 and 20 against 60 for sales. Yet the portion of the market participant that uses the website appears to be enough to consider my measure as significant. On the market tightness itself, i.e. the buyer-seller ratio, it almost never exceeds 1 that *a priori* could be expected to be some kind of equilibrium level. As mentioned before and detailed in table 2, despite this seemingly low market tightness, Paris area housing market experienced a rise in the 2016-2017, which can be considered as contradictory. Two interpretations can be made of this, either MeilleursAgents.com reach more sellers than buyers or the pivot point is significantly lower than 1, around 0.6. Buyers being informally disadvantage in the housing market, it seems odd to me to believe that they would stay almost 2 time less on the market than sellers at equilibrium. Thus I favor the second hypothesis. Because *MeilleursAgents.com* business model is entirely based on sellers, one could easily imagine they optimized their acquisition funnels toward them, thus biased the market tightness measure proposed here. That would not cause any issue later in my econometric analysis as I use only logged market tightness. Under the hypothesis that this seller leaning bias is constant over time and across Paris area cities, it would only impact the constant.

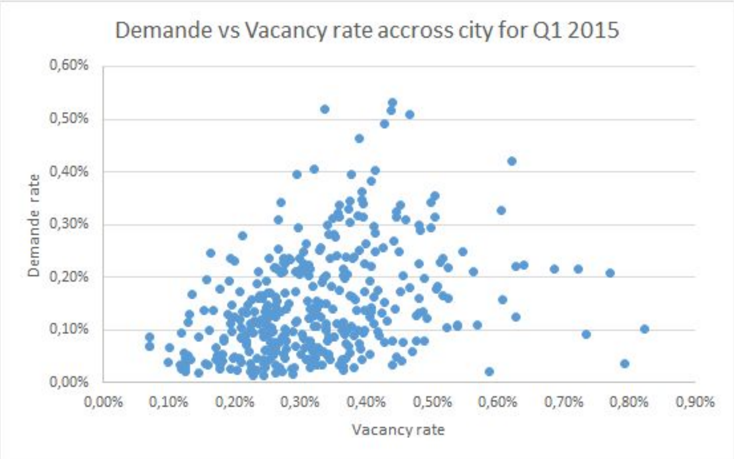
The main market indicators averages computed yearly and quarterly are presented in table 2. Note that here are presented the unweighted average of all segment, thus the 1,000 apartments in Chevy (my smallest segment) weight just as much as Paris 15th arrondissement.

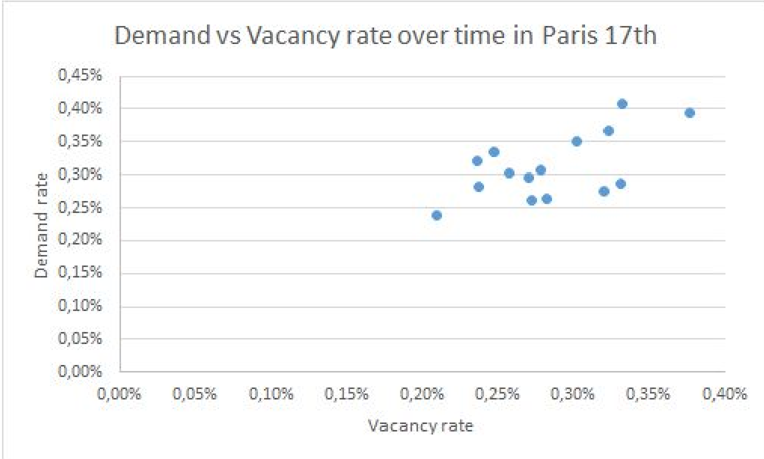
As mentioned before, two quasi symmetrical periods can be identified as far as the price dynamics is concerned: they declined in 2014-2015 then bounced back in 2016-2017 to return to their initial level. During the whole 4 years period volumes, i.e. the rotation rate increase constantly, despite seasonal variations (the market seems more dynamics in Q2 and less in Q4). This price variation - volume correlation was expected as it is a well documented phenomena in the real estate market (see Stein, 1995 and Genovese and Mayer, 2001). Another particularly satisfying, and this time new in the real estate litterature, is the apparent covarition of volume and market tightness. This particular fact will be more deeply study in the section 4 of the present paper.

	average market tightness	average rotation rate	average price index	average quarterly price variation	average vacancy rate	average demand rate
2014	**0,46**	**0,52%**	**98,7**	**-0,56%**	**0,28%**	**0,12%**
Q2	0,45	0,57%	99,2	-0,51%	0,30%	0,13%
Q3	0,46	0,51%	98,7	-0,58%	0,25%	0,11%
Q4	0,47	0,47%	98,1	-0,61%	0,29%	0,12%
2015	**0,55**	**0,55%**	**97,3**	**-0,20%**	**0,28%**	**0,14%**
Q1	0,48	0,53%	97,6	-0,42%	0,34%	0,15%
Q2	0,58	0,64%	97,3	-0,14%	0,30%	0,16%
Q3	0,58	0,57%	97,2	-0,11%	0,24%	0,13%
Q4	0,57	0,46%	97,0	-0,10%	0,23%	0,12%
2016	**0,62**	**0,61%**	**97,2**	**0,17%**	**0,27%**	**0,15%**
Q1	0,55	0,54%	96,9	0,02%	0,31%	0,15%
Q2	0,61	0,64%	97,0	0,19%	0,29%	0,17%
Q3	0,64	0,60%	97,3	0,22%	0,22%	0,13%
Q4	0,67	0,65%	97,5	0,26%	0,24%	0,15%
2017	**0,68**	**0,68%**	**98,7**	**0,58%**	**0,25%**	**0,15%**
Q1	0,65	0,72%	97,8	0,44%	0,27%	0,16%
Q2	0,67	0,75%	98,4	0,76%	0,26%	0,16%
Q3	0,70	0,69%	99,2	0,64%	0,21%	0,13%
Q4	0,70	0,58%	99,6	0,49%	0,25%	0,16%

Table 2 : Market indicators averages over time

The increase in market tightness at the aggregated level seems to be the output of a drop in the vacancy rate combined with an increase in the demand rate (i.e. active buyers per units in the segment). This negative supply / demand correlation would be the housing equivalent of the labor market famous Beveridge Curve. Figure 1 and 2 present relationships between vacancy and demand across segment at a given date and over time for a given segment. Table 3 shows statistics for this correlation for all segments and dates (for correlation within segments, I only consider those with datapoint for at least half of the periods).





	count	mean	std	min	25%	50%	75%	max
Cross segment correlation	15	0.29	0.06	0.17	0.25	0.31	0.33	0.38
Cross period correlation	395	0.12	0.30	-0.65	-0.10	0.12	0.33	0.92

Table 3: Correlation between demand and vacancy rate across segment and across period

Far from the labor market Beveridge Curve, demand and vacancy rather exhibit a positive correlation. Such an “inverse Beveridge Curve” for the housing market has been documented by Piazzesi and al. (2015) and find conformation here as I find a positive correlation across segment for all periods and across date for most segments. A first explanation of this positive correlation could be that unlike labor market participants, companies and private persons, homesellers and homebuyers can be and often are on both side of the market at the same time as owners often sell their home to buy a new one.

IV. Empirical results

The dataset described above allow to verify if theoretical results about the effect of market tightness on price and volume. More precisely I studied the impact of the logged buyer-seller ratio on three market outputs: the logged quarterly rotation rate, the logged price index and the relative price variation. The real estate market is subject to strong seasonal effect, thus I control for it, taking Q1 as reference. Apartments and standalone houses represent different markets : investors focus on apartments, houses tend to be larger, Paris’s city center is almost exclusively composed of apartments, distant suburbs are almost only composed of houses, etc… As a consequence I control also by the item type of the segment. To assess if the effect of market tightness is symmetrical in “hot” and “cold” market, I also regress the 2014-2015 period (cold market) and the 2016-2017 on (hot market) separately. Finally I also introduced the lagged market tightness (i.e. the buyer-seller ratio in the segment in the previous quarter) in my regression in order to test for the market reactivity to change in the tightness.

Formally I performed OLS regression of the following formula :

$$log(Rotation\ Rate) \sim log(market\ tightness) + log(market\ tightness\ lagged) + \sum_{i=2}^{4} {}_{Q=i} + {}_{type=house}$$

$$log(price\ index) \sim log(market\ tightness) + log(market\ tightness\ lagged) + \sum_{i=2}^{4} {}_{Q=i} + {}_{type=house}$$

$$log(price\ variation) \sim log(market\ tightness) + log(market\ tightness\ lagged) + \sum_{i=2}^{4} {}_{Q=i} + {}_{type=house}$$

Table 4 a to c presents my results :

Dependant variable: logged(quarterly rotation rate)						
	model	model with lag	model 2014-2015	model 2016-2017	model log > 10k	model log > 10k lag
intercept	-5.1409 (-323.327)	-5.1265 (-313.168)	-5.2722 (-189.048)	-5.0782 (-256.452)	-5.2040 (-207.759)	-5.1935 (-206.497)
market tightness	0.0711 (8.805)	0.0532 (5.624)	0.0410 (2.971)	0.0407 (3.220)	0.1632 (10.556)	0.0920 (3.546)
market tightness lagged		0.0343 (3.618)	0.0254 (1.825)	0.0227 (1.812)		0.0881 (3.412)
item type house	-0.0623 (-4.910)	-0.0641 (-5.059)	-0.0290 (-1.578)	-0.0908 (-5.377)	-0.0346 (-0.774)	-0.0278 (-0.622)
Q2	0.0908 (5.102)	0.0926 (5.204)	0.1492 (5.318)	0.0936 (4.113)	0.0391 (1.272)	0.0401 (1.308)
Q3	-0.0283 (-1.581)	-0.0287 (-1.602)	0.0078 (0.274)	-0.0069 (-0.303)	0.0209 (0.679)	0.0213 (0.693)
Q4	-0.1053 (-5.870)	-0.1055 (-5.887)	-0.1207 (-4.253)	-0.0349 (-1.526)	-0.0757 (-2.457)	-0.0712 (-2.317)
R^2	3.9%	4.2%	5.7%	2.7%	7.7%	8.4%

Table 4-a: Impact of market tightness on rotation rate

Dependant variable: logged(price index)						
	model	model with lag	model 2014-2015	model 2016-2017	model log > 10k	model log > 10k lag
intercept	-0.0167 (-12.603)	-0.0126 (-9.388)	-0.0210 (-13.633)	-0.0064 (-3.256)	0.0024 (0.900)	0.0046 (1.781)
market tightness	0.0138 (20.581)	0.0088 (11.296)	0.0025 (3.233)	0.0140 (11.113)	0.0286 (17.625)	0.0131 (4.883)
market tightness lagged		0.0097 (12.411)	0.0032 (4.112)	0.0152 (12.082)		0.0192 (7.153)
item type house	0.0040 (3.787)	0.0035 (3.331)	0.0049 (4.823)	0.0017 (1.002)	-0.0065 (-1.376)	-0.0050 (-1.075)
Q2	0.0052 (3.486)	0.0057 (3.871)	0.0061 (3.958)	0.0033 (1.447)	0.0066 (2.054)	0.0068 (2.155)
Q3	0.0060 (4.051)	0.0059 (4.039)	0.0030 (1.923)	0.0070 (3.071)	0.0104 (3.211)	0.0105 (3.287)
Q4	0.0055 (3.715)	0.0055 (3.730)	-0.0007 (-0.450)	0.0094 (4.099)	0.0096 (2.953)	0.0105 (3.304)
R^2	7.9%	10.3%	4.2%	17.1%	17.9%	20.5%

Table 4-b: Impact of market tightness on price level

Dependant variable: logged(quarterly price variation)						
	model	model with lag	model 2014-2015	model 2016-2017	model log > 10k	model log > 10k lag
intercept	0.0028 (8.025)	0.0037 (10.220)	-0.0021 (-4.062)	0.0058 (12.584)	0.0074 (9.894)	0.0079 (10.524)
market tightness	0.0032 (17.670)	0.0021 (10.078)	0.0012 (4.773)	0.0020 (6.887)	0.0061 (13.103)	0.0029 (3.732)
market tightness lagged		0.0020 (9.782)	0.0011 (4.270)	0.0020 (7.017)		0.0039 (5.113)
item type house	-0.0002 (-0.549)	-0.0003 (-0.951)	0.0008 (2.173)	-0.0010 (-2.681)	-0.0007 (-0.509)	-0.0004 (-0.283)
Q2	0.0005 (1.295)	0.0006 (1.572)	0.0009 (1.671)	0.0023 (4.413)	0.0011 (1.166)	0.0011 (1.224)
Q3	0.0002 (0.546)	0.0002 (0.498)	0.0006 (1.154)	0.0017 (3.307)	-0.0016 (-1.699)	-0.0015 (-1.695)
Q4	-0.0002 (-0.431)	-0.0002 (-0.462)	0.0005 (0.966)	0.0010 (1.930)	-0.0020 (-2.198)	-0.0018 (-1.994)
R^2	5.3%	6.9%	3.4%	7.1%	10.9%	12.4%

Table 4-c: Impact of market tightness on price variation

The first and main result is that, in line with what theory predicted, I find a positive, strongly significative effect of market tightness on volume, price and price variation. Note that this effect remain positive and significant for all my regressions: with and without lagged market tightness, in hot and cold market periods. However the coefficients remain surprisingly weak in absolute value as, for example in the simplest model, a buyer to seller ratio that doubles only increase the sales volume of 5% and price by 1%. A simple explanation could be find in the important variance of volume as the quarterly rotation rate in my sample are spread from 0.05% to more than 4% mainly because of some small segments. As I focus on large segments, the ones composed by at least 10,000 units, the magnitude of the effect of market tightness on rotation rate, price and price variation is roughly doubled.

Another result that are consistent for almost all my regression is that the lagged market tightness, i.e. the ratio of the previous quarter, has a positive and significant effect on volume and price. In the case of the rotation rate, the effect of the lagged buyer-seller ratio appears weaker than the not lagged one. In contrast, for price and price variation, the lagged one has an equal or stronger effect. One interpretation could that because the market tightness measure proposed here is not perfect, to add the lagged one allow some kind of smoothing that make it more robust. However this could be more profound, in particular the fact that volume seems less sensitive than price to the lagged market tightness is somehow appealing. Real estate prices variation tend to be temporarily autocorrelated (see for example Case and Shiller, 1988) as sellers and buyers, but also professional real estate agents, rely on recent sales or listings in their valuation process thus in could take time for market conditions to be reflected in prices, whereas for volume the matching process is more mechanical and the size of the sellers and buyers populations affect it more rapidly.

In that perspective the comparison between the models fitted on 2014-2015 data (cold market) and the ones based on 2016-2017 data (hot market) is insightful. Effect of market tightness, up to date and lagged, on rotation rate appear very similar in both phases of the cycle. Prices, on the other hand, have a differentiated reaction to market tightness during the two periods. In the effect of buyer-seller ratio in the “bust” period is weaker and less significative than during the “boom” phase. Here it may be assume that sellers are more eager to react to market conditions when it can help them to justify an increase in price than the other way around, but it is harder for them to influence their matching rate as it is more directly link to the market tightness.

V. Conclusion

Using a dataset built through users’ activity on the internet real estate plateforme *MeilleursAgents.com*, I track the vacancy rate, demand rate, and market tightness, evolutions over a four years period, on a quarterly basis, of housing markets for more than 250 municipalities of the Paris Area. I am able to confirm the upward sloping Beveridge curve across segment, already documented in the litterature. I also observe the same phenomena for most segments across time. This study is the first to estimate a matching function in the real estate market using a direct measure of the market tightness. As predicted by the theoretical literature, I measure a positive statistically significant impact of market tightness on volume, price and price variation. Interestingly, the market tightness affects more directly volumes than prices that seems to react with a lag.

Extensions of the present work are plenty. For example, using the same dataset, one could try to measure what factors impact the matching efficiency from one market to another. Mismatch between the buyers wish and the reality of the offer in term of housing amenities for example. The integration between the markets here studied open also interesting perspectives. In particular, it would be particularly insightful to observed how the integration of a segment within the larger market mitigate or accentuate its reactions to demand shock.

Despite participating to the so far too thin empirical literature on search and matching for the housing market, this work aims at bringing another proof that data collected on the internet can enable us to answer open questions. As the share of economic activities that occurs on-line growths, such opportunities to confront theories with hard facts would growth as well.